Agreement Level Among Online Investors in Indonesian Stock Exchange

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Abstract

Social media such as Twitter is a online platforms to exchange stock information. Many researchers believe that more information about the stock market should reduce volatility. This study aims to see the impact of agreement among investors in the capital market moderated by investor alpha. Is it only considered noise or valuable information? We used data on Twitter to capture agreement among investors and the impact of investor alpha from 2016 to 2021 and analyze 10242 stock-related daily messages using computational linguistics and examine the mechanism leading to an efficient aggregation of information from investor alpha or quality of investment advice based on 60 largest trading volume stock registered in Indonesia Stock Exchange. We used the moderation model PROCESS analysis regression to seek to determine whether the size or sign of the effect agreement among investors in the capital market depends in one way or another on the quality of investor alpha. Our results show that disagreement among online investors positively correlated with volatility and the impact of agreement among investors on volatility in the capital market depends on the quality of investor alpha. In other words, the level of agreement between investors can affect the volatility of the stock market depending on the accuracy of the recommendations given by alpha investors on the stock returns for a period.

Keywords
Volatility, Disagreement Investors, Investor Alpha, Behavioral Finance,

1. Introduction
The development of the internet has had an impact on every piece of information received by investors, especially investors who seek the information through social media platforms. Previous empirical studies reveal that investors are often influenced by word of mouth (Ng and Wu, 2006; Mizrach and Weerts, 2009). Cao et al. (2002) state that if

investors receive the same signal, it makes them more likely to trade or stock transactions, where a larger deal on a given day will be followed by more trades the next day and a bigger disagreement on one day predict fewer trades the next day, not more trades (Antweiler and Frank, 2004). Where agreement level relates to message volume while message volume relates to trading volume.

Hong and Stein (2005) on the "disagreement model", argue that increasing trading volume and momentum indicates disagreement among investors and release more information (Das et al., 2005). In financial theory, there are two different perspectives on the disagreement between investors, the traditional hypothesis and the no-trade theorem (Antweiler and Frank 2004). In the traditional hypothesis, disagreement induces trading while the no-trade theorem argues that disagreement leads to market revision and beliefs. The beliefs among investors can cause volatility in the market investors (Jones et al., 1994).

Initially, Sprenger et al (2014) argued that there was a positive relationship between a disagreement among investors and volatility in the market, but from the results of the research conducted, it was concluded that the higher the level of volatility in the market contributed to the disagreement among but not vice versa. This means that it is volatility in the market that causes disagreements between investors. Based on data released by yahoo finance, the stock market in Indonesia during the last five years has high volatility so that this has a major impact on disagreements among investors.

In psychology, personality plays an important role in determining the behavior and performance of investors in the stock market (Borghans et al., 2008). It is undeniable that information disclosure makes investors tend to follow the information provided by expert investors or investors who provide quality information. Social media is a platform that makes it easy for investors to get information from it (Bar-Haim, 2011). The quality of the information provided by expert investors online can be seen through the prediction of stock returns or known as investor alpha (Sprenger et al., 2014). From this research, it can be concluded that when quality information is spread among investors, an agreement can occur between investors.

1.1 Objectives

The increasing use of social media in Indonesia, especially on the Twitter platform which is widely used by online investors or what is known as investor microblogging, provides an alternative information search that can be accessed by individual investors who have been considered difficult to obtain information about the money market, thus causing the occurrence of information asymmetry. However, the information circulating by online investors can affect the volatility of the stock market. In addition, the quality of alpha investor information followed by online investors to make investment decisions in the stock market is also considered to affect the behavior of investors. So the aims of this study is to find out whether the level of agreement between online investors affects volatility in the stock market in Indonesia, where this effect will depend on the quality of alpha investor information followed by online investors.

2. Literature Review

Cognitive bias is correlated between investors and market prices. Behavioral finance has the potential to explain not only how people make financial decisions and how markets function but also how to improve them. The human mind tends to relate social outcomes to individual actions. One example of investment socialization is the investment group, through this group, individual investors discuss stock investments that have the potential to generate profits. It is known that investment behavior in the group shows the same psychological bias as individual investors (Nofsinger, 2005). However, social dynamics have an important role in the success of individual investors, so changes in stock prices are influenced by social dynamics (Shiller, 1984).

The model of disagreement put forward in the stock market by Hong and Stein (2005), where investor confidence is often a simple function of their own priors and signals they observe directly. When there is information received in advance by investors, these investors will adjust their valuation of the shares they own, while investors who do not know this information will not make changes to the valuations of the shares they have, thus creating disagreements between investors, the result is that the first investor will buy from the final group.

In other words, disagreements between investors will lead to an increase in trading volume. Using investor microblogging (Antweiler and Frank, 2004), also provides the same evidence that disagreements among online investors can lead to an increase in trading volume. Das and Chen (2005) state that disagreements about market information lead to extensive debate and generate more information. While Sprenger et al. (2014), also uses investor microblogging and argues that disagreements among online investors can lead to an increase in trading volume.

The more information circulating among investors is said to be able to reduce the level of volatility in the stock market (Danthine and Moresi, 1993). As we know, high volatility indicates that a market is moving in a large range. Stock prices overreact to private information signals and underreact to public signals. Shows that this overreaction-correction pattern is consistent with long-term negative autocorrelation in stock returns, unconditional excess volatility (unconditional volatility is more than would be obtained with a fully rational investor), and with further implications for signal type-dependent volatility. Markets will tend to overreact or underreact to different types of information which allows investors to overcome the remarkable pattern that the average return on announcement dates across nearly all event studies is of the same sign as the average post abnormal return (Daniel et. al, 1998).

The biggest part of today's social environment is media, especially social media nowadays. Information circulating on social media platforms is information that rolls quickly, is open, and is easily accessible by anyone at any time. So it can be said that social media currently influences every decision that will be taken, especially by individual investors. Antweiler and Frank (2004) conclude that Internet stock message boards help predict market volatility. Currently, many researchers have researched the behavior of investors that can influence the stock market through Twitter, which is one of the platforms for social media in the form of microblogging. The method used to calculate the level of agreement between investors on Twitter according to Sprenger et al. (2014) is as follows:

$$At = 1 - \sqrt{1 - \begin{matrix} MBuyct - MSellct \\ MBuyct + MSellct \end{matrix}}$$

Where
At = Agreement Level period t
MBuy = Number of Messages converted into a “buy” signal
MSell = Number of Messages converted into a “sell” signal

If all messages are bullish or bearish, then the level of agreement between investors is equal to one, otherwise there is disagreement between investors.

In calculating the quality of information provided by quality investors or called alpha investors, to find out whether alpha investors have an influence on investor sentiment, each tweet or post will be classified as "buy", "sell", and "hold" as a signal. , 0, and -1 (Zhang et al., 2009). With the quality index as follows:

$$quality = \begin{cases} = 1 \; if \; \dfrac{Sit}{Rit} & > 0 \\ = 0, Otherwise & \end{cases}$$

Sit = Investor sentiment in period t related to a particular stock
Rit = Relative Return on the same day as investor sentiment
This results in whether the messages shared by investors are of high quality or not.

Previous empirical studies reveal that investors are often influenced by word of mouth (Ng and Wu, 2006; Mizrach and Weerts, 2009; Hong and Stein, 2005). Boyd et al. (2010) have suggested that users frequently retweet messages to convey valuable content to validate and support a particular user or post and the number of followers may correlate with the accuracy of published information (Giller, 2009). Microblogging investor have an incentive to publish valuable information to maintain or increase their mentions, retweet rates, and followers which affects the diffusion of information in microblogging forums and provides a mechanism for readers to weigh in on the information.

According to (Hong and Stein, 2005) it can be explained in the "disagreement model" where increasing momentum and trading volume indicates disagreement among investors, besides that positive information, will be received by investors differently so that ultimately there is a disagreement between investors which causes an increase in trading volume. If there is an agreement between investors, it shows an underreaction reaction or the condition of the investor is in a sluggish or bearish state where the disposition effect has a large impact on this condition (Frazzini, 2006).

Cao et al. (2002) state that if investors receive the same signal, it makes them more likely to trade or stock transactions, where a larger deal on a given day will be followed by more trades the next day and a bigger disagreement on one day predict fewer trades the next day, not more trades (Antweiler and Frank, 2004). Where agreement level relates to message volume while message volume relates to trading volume.

From the explanation above, the research model and the hypothesis of this research are as follows (Figure 1)

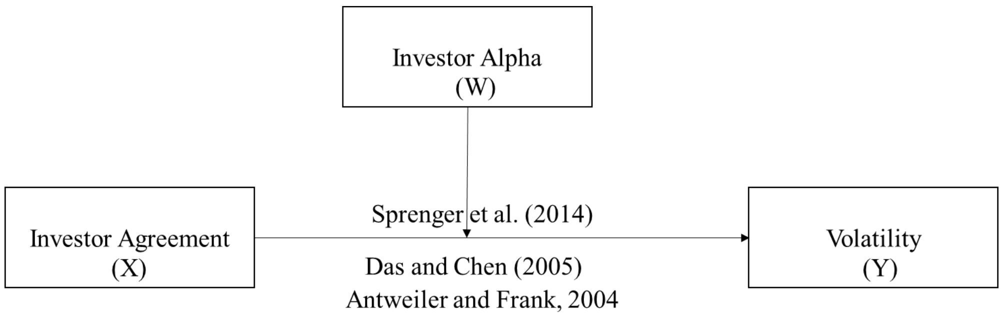

Figure 1. Research Model

Hypothesis 1 : Increased disagreement among stock microblogs is associated with higher volatility.
Hypothesis 2 : Increased disagreement among stock microblogs is associated with higher volatility depends on the quality of investor alpha.
Hypothesis 3 : The quality of investor alpha has a conditional effect on higher volatility.

The operational variables used in this study are as follows: (Table 1)

Table 1. Operational Variables

Operational Variables	Concept Variables	Scale/Measurement
Volatility	Stock volatility is the result of calculating the annual standard deviation which is intended to measure stock risk in the next period using previous research Sprenger et al. (2014).	Ratio
Investor Agreement	Is the level of agreement between investors posting information on Twitter (Hong and Stein, 2005; Sprenger et al., 2014)	Ratio
Investor Alpha	Are investors who provide quality posting on Twitter according to Sprenger et al. (2014).	Ratio

3. Methods

This study focuses on the level of agreement that occurs when viewed from information in the form of tweets shared by online investors on Twitter social media or what is known as investor microblogging. All information in the form of tweets uploaded by individual investors is captured based on the #sharecode embedded in each tweet made. This level of agreement between investors is used to see whether the information provided by each investor and posted online has an effect on the level of capital market volatility and whether expert investors who are sources of information for other investors also affect the level of investor agreement on volatility.

The data collection method was carried out in two stages, namely secondary data and data mining, data mining sampling technique used was based on the research of Oh and Sheng (2011). The system used is a pipeline system, namely there are 5 important phases carried out in data mining retrieval, namely:

Step 1 Download data,
Step 2 Pre-processing,
Step 3 Sentiment Analysis,
Step 4 Prediction classification,
Step 5 Evaluation and analysis.

Information comes from posts and is not explicitly provided by the author, data extraction must be done manually and automatically. To examine the relationship between signals from stock microblogs, the key signal classifications “Buy” and “Sell” and “Hold” were used. Because the data set contained too many messages for manual coding, it was chosen to classify messages automatically using well-established methods of computational linguistics. In line with Antweiler and Frank (2004), using the Naïve Bayesian classification method, one of the most widely used algorithms for text classification. Naïve Bayesian classification to categorize each tweet and weigh the tweets based on the level of trust based on the weighted number of positive and negative tweets and tweet volume (Bartov, et al., 2015).

While alpha investors or those who consistently provide quality advice and have an influence on investors, the indication is through tweets or posts that they will be classified as "buy", "sell", and "hold" as signals 1, 0, and -1 (Zhang, 2009). In measuring the quality of investors, the approach taken by Sprenger et al. (2014). Each upload or "tweet" on twitter is classified into recommendations "buy", "hold", "sell", then the signal is converted to 1, 0, -1. The definition of tweet quality is the accuracy of the recommendations given by online investors on stock returns in period t. If the value of the signal compared to the rate of return in period t is greater than zero, then the quality is worth one, otherwise if it is less than zero, the quality of the investor is zero.

4. Data Collection

The data used in this study was carried out in two stages, namely using secondary data and data mining through twitter. Adapun penjelasan dari setiap data adalah sebagai berikut:

1. Secondary Data
   The type of secondary data used in this study is volatility data from all stocks with the largest number of assets listed on the Indonesia Stock Exchange for the 2016 – 2021 sample period.
2. Data Mining
   Data mining aims to extract keywords taken from the conversation platform on Twitter which are commonly used in the form of "hastags" or results which are usually keywords that are included in many messages to be associated or called "tags" stock codes based on 60 largest trading volume stock registered in Indonesia Stock Exchange sample period 2016 – 2021. Furthermore, all existing information in every upload made by online investors will be converted into Buy", "Sell" and "Hold" signals so that later can be calculated the level of agreement between investors on Twitter and In calculating the quality of the information provided by quality investors or called alpha investors.

The sampling data collection process uses an approach to the technique carried out by Oh et al. (2011) which consists of five stages. Furthermore, message classification is carried out using the Naïve Bayesian classification method, one of the most widely used algorithms for text classification. Naïve Bayesian classification for categorizing each tweet and weighing tweets based on the level of trust based on the weighted number of positive and negative tweets and tweet volume (Antweiler and Frank, 2004; Bartov, et al., 2015). The method that underlies the Naïve Bayesian classification used is in accordance with the approach taken by Sprenger et al. (2014).

The results of text classification using the Naïve Bayesian classification for categorizing each tweet and weighing tweets based on the level of trust based on the weighted number of positive and negative tweets and tweet volumes are as follows:

Table 2. Manual Clasiffication – Training Set

Sample Tweet	Manual Clasiffication
2015 BNI Syariah Net Profit Increases 39.98 Percent	Buy
Ciputra's Profits Are Beaten	Sell
CTRA PROFIT: Grows 35.6%, Ciputra Development Reaches Rp1.32Trillion	Buy
In the meantime, let's watch first, while also watching on #ADRO, #PTBA	Hold
#PTBA #ADRO is holding on for a while, there is still hope for a rally	Hold

Table 3. Automatic Tweet Clasiffication

Tweet	Buy	Hold	Sell
ADRO Net Profit Grows 2.4%	100%	0%	0%
Profit Down 21%, Adaro Fixed Dividend Divided Rp 981 billion	73%	20%	7%
#BBCA while corrections can be collected / buy on weaknesses	97,3%	0,7%	2%
Will the next quarter of #ASII sales go up or down?	0%	89,1%	10,9%
#BBRI why is it even landslide	0%	8,7%	91,3%

From the data (Table 2 & 3) above, to determine the level of consistency between the manual classification and automatic classification methods, the Cohen's Kappa test was carried out. From the results of the calculation of the correlation, a value of 0.572 and consistency testing between the two measurement methods through the Cohen's Kappa test resulted in a value of 0.657 with a significance of 0.000, this indicates that there is a correlation between the two approaches and the Cohen's Kappa test value which is close to one is an indicator that shows that the assessment using the training dataset and the manual is mutually consistent.

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$Y = \mathrm{iy} + \mathrm{b1X} + \mathrm{b2W} + \mathrm{b3XW} + \mathrm{ey}$..........1

Where :
Y : Volatility
X : Agreement Among Investors
W : Investor Alpha

Also, the statistical diagram can be seen in the following image :

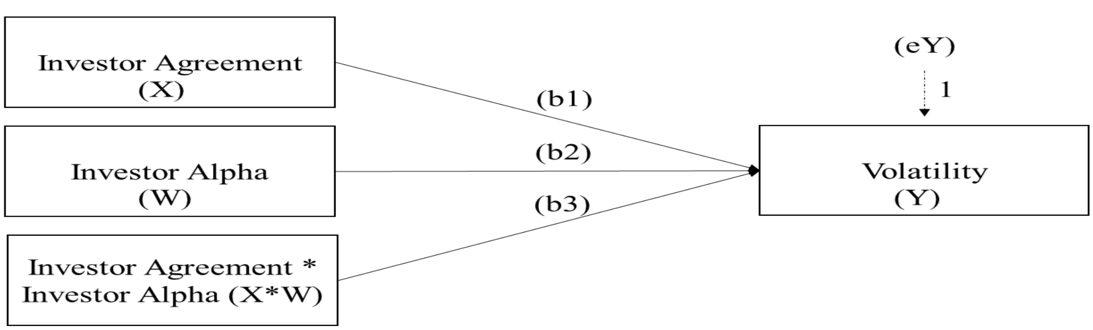

Figure 2. Statistical Diagram

5. Results and Discussion

5.1 Statistical Results

The model used in this study is free from perfect collinearity and heteroscedasticity by transforming the data using the mean-center and the output using the heteroscedasticity-consistent covariance estimators test in PROCESS version 3.5 with the statement A "heteroscedasticity consistent standard error and covariance matrix estimator was used". According to Hayes (2018), if the research conducted focuses on knowing the effect of the moderator variable on the independent variable, then the same results will be obtained with or without transforming the data using the mean-center. So it can be concluded that the model used is best linear unbiase estimate.

The following is the result of data processing using the moderation model PROCESS analysis regression to seek to determine whether the size or sign of the effect agreement among investors in the capital market depends in one way or another on the quality of investor alpha.

Table 4. Model Summary

R	R-sq	F(HC0)	MSE	df1	df2	p
,0651	,0042	,0003	16,8196	3,0000	10529	,0000

In Table 4. it can be concluded that in this study an R^2 of 0.0042 or 4.20% was produced. This shows that the level of investor agreement on the volatility of the capital market in Indonesia is moderated by the quality of the information provided by investor alpha of 4.2% and the rest is influenced by other variables. This means that disagreements that occur in microblogging investors whose influence depends on the quality of alpha investors affect 4.2% of increase volatility in the capital market.

From the results of model, it can be concluded that increased disagreement among stock microblogs is associated with higher volatility significant at = 0.00 with a coefficient value of 0.0027, this also answers the first research hypothesis or H1. Where every time there is an increased disagreement among stock microblogs investors, the volatility of the capital market will increase. This is in line with the research conducted by Sprenger et al. (2014) which states that a increase disagreement among stock microblog investors is associated with higher volatility.

In addition, it is also known that the conditional effect of the quality of alpha investors does not affect the increase in volatility in the capital market in Indonesia, as can be seen from the results of p = 0.5071 with a coefficient = -0.000000069 if there is no level of agreement between microblogging investors. This also answers Hypothesis 3: The quality of investor alpha has a conditional effect on higher volatility, meaning that Hypothesis 3 is rejected, quality of investor alpha has no conditional effect on higher volatility provided that there is no level of agreement between investors.

Table 5. Research Model

	coeff	se(HC0)	t	p	LLCI	ULCI
constant	,0222	,0002	139,7599	,0000	,0219	,0225
AG	-,0027	,0004	-6,8014	,0000	-,0034	-,0019
IA	-,00000069	,00000113	,6635	,5071	-,00000291	,00000153
Int_1	,00000330	,00000195	1,6941	,0903	-,00000052	,00000713

The best-fitting model produced in this research is as follows:

$$Y = 0{,}0222 - 0{,}0027X - 0{,}00000069\mathrm{W} + 0{,}00000330\,\mathrm{XW} \quad \ldots\ldots 2$$

From the best-fitting model produced in this research, if there is an increase of one unit in disagreement among investors, then volatility will increase by 0.0027 or if there is an increase in agreement among investors, then volatility will decrease by 0.0027. This condition can also occur when expert investors or called alpha investors do not provide quality information. However, quality information from investors alpha does not have a conditional effect on increasing volatility when there is no agreement between investors. In addition, if there is an increase of one unit on the interaction between the Investor Agreement and the quality of Investor Alpha, it will cause an increase in volatility in the capital market by 0.00000330, this shows that the size of the influence of microblogging Investor Agreement on increasing volatility in the capital market depends on the quality of information. provided by alpha investors.(Table 5)

Table 6. Test(s) of Highest Order Unconditional Interaction

	R2-chng	**F(HC0)**	**df1**	**df2**	**p**
X*W	,00013748	2,8698	1,0000	10529	,0903

However, if seen in Table 6. it can be seen that the size or sign of the effect agreement among investors in the capital market depends in one way or another on the quality of investor alpha. It can be seen from the value of $p = 0.0903$ at coefficient = 0.00000330 at significant at $p < 0.10$. This also answers Hypothesis 2: Increased disagreement among stock microblogs is associated with higher volatility depending on the quality of investor alpha. In this case, increasing disagreement among investors causes volatility, moderated by investor alpha. This component of the model explains 0,014% an equivalent test of interaction between increasing disagreement among investors and the quality of investor alpha.

5.2 Graphical Results

The following is a graph showing the conditional effect of agreement among investors about the increase of volatility moderated by investor alpha. Describe the Conditional Effect of the Focal Predictor from the moderation model used in this study. The following Figure 3 shows the magnitude of the effect of the moderating variable, namely investor alpha, on the effect of the level of investor agreement on the level of volatility.

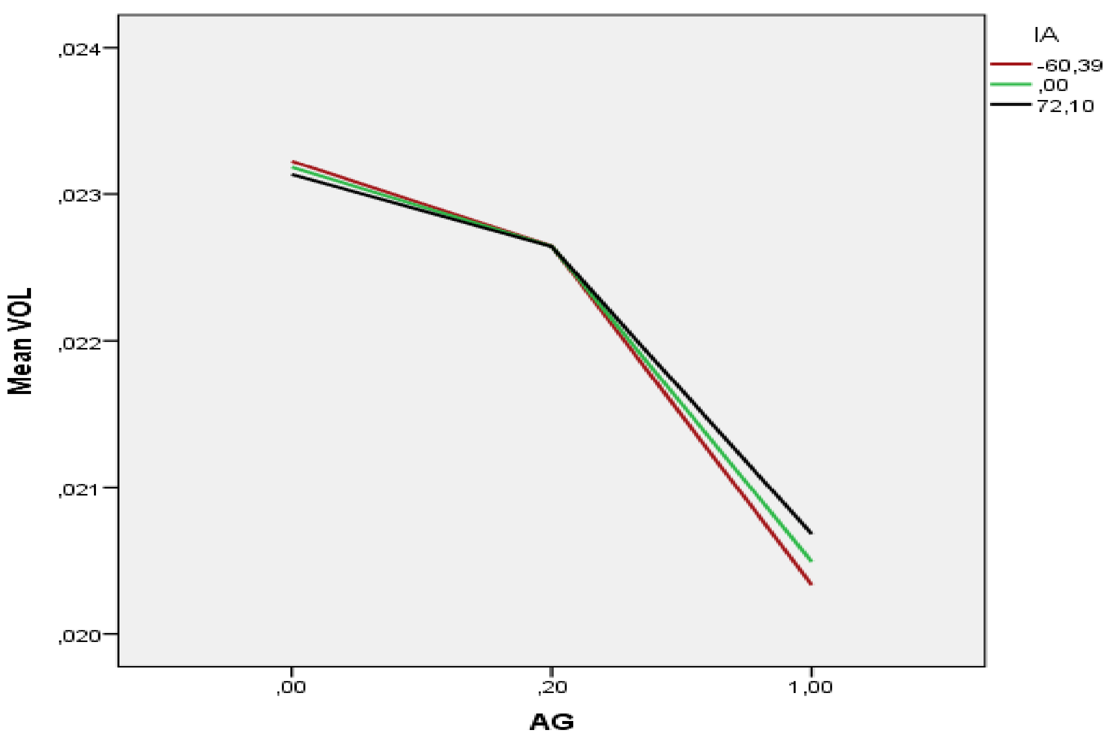

Figure 3. Conditional Effect of Focal Predictor

From Figure 3. it can be seen that there is a difference in the impact given of volatility on changes in the level of agreement between online investors and the quality of the information provided by alpha investors. When a disagreement occurs between investors, it will cause an increase in volatility where the size of the impact will depend on the quality of the information provided by the alpha investor. When the information provided by alpha investors is not of good quality, it will cause a higher level of volatility, but if the information provided is of good quality, it will cause a decrease in the level of volatility when there is a disagreement between investors.

When there is an agreement between investors that will cause a decrease in the level of volatility. This condition will be different depending on the quality of the information provided by alpha investors. When the quality of the information provided causes a higher level of volatility than when there is a decrease in the quality of information. The quality of this information is seen from how valid the level of information provided by alpha investors is as compared to the realization of returns in period t.

5. Conclusion

This study has a purpose to see the effect of agreement among online investors which we called microblogging investors on volatility in the stock market in Indonesia where the size of the effect depends on the quality of the information provided by alpha investors. Alpha investors are investors who provide information about the level of "buy", "sell", and "hold" which is compared to the condition of the rate of return in period t. It is said to be qualified when the information is by the conditions that occur in the stock market. The results showed that the increase in disagreement among online investors led to an increase in the level of stock market volatility even though there was no information provided by alpha investors. However, alpha investors themselves do not have a conditional effect on the level of volatility when there is no agreement or disagreement between online investors. However, the size of the effect of the level of agreement between online investors on the level of volatility will depend on the quality of alpha investors. The impact given will be different depending on the quality of the information provided by the alpha investor, When a disagreement occurs between investors, it will cause an increase in volatility where the size of the impact will depend on the quality of the information provided by the alpha investor. When the information provided by alpha investors is not of good quality, it will cause a higher level of volatility, but if the information provided is of good quality, it will cause a decrease in the level of volatility when there is a disagreement between investors. But when there is an agreement between investors that will cause a decrease in the level of volatility. This condition will be different depending on the quality of the information provided by alpha investors. When the quality of the information provided causes a higher level of volatility than when there is a decrease in the quality of information.

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